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Experimental research of online monitoring and evaluation method of human thermal sensation in different active states based on wristband device

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ABSTRACT

Existing automatic control of building thermal environments do not consider the individual's real-time thermal sensation, which could reduce the occupants' thermal comfort. Therefore, it is very important to accurately obtain an individual's thermal sensation and real-time reflect on the control logic of air-conditioning systems. Current thermal sensation estimation models mostly apply to sedentary condition without considering human sensation in different activity states, which caused these models have critical limitations in accurately predicting human thermal sensation. In this paper, an intelligent wristband device is used for online monitoring of human thermal characteristics in different active states. The wrist skin temperature and its time differential as well as the heart rate are used for the evaluation index of human thermal sensation, and a series of environmental chamber experiments are carried out to obtain the relationship between the wrist skin temperature and thermal sensation in different activity states in summer. The correlation models of human thermal sensation, wrist skin temperature and its time differential, and heart rate has been formulated by statistical analysis and correlation analysis. In order to verify the feasibility of correlation models in the unstable environmental condition, several tests were conducted in the actual built environment. This study indicates that the wrist skin temperature and its time differential and heart rate can be used for estimating human thermal sensation with a high degree of accuracy in the different activity states. In addition, results of this study also demonstrate the promising applicability of obtained correlation models in the unstable environmental condition.

1. Introduction

The building thermal environment does not only impact the comfort and health of the human body, but also impacts the building's energy consumption and pollutant emission. The automatic control of the building thermal environment should be based on meeting the requirements of human thermal comfort. However, the default setting of existing building thermal environment generally determined by relevant design criterion and the automatic control systems of heating, ventilation and air-conditioning (HVAC) systems are usually based on the assumption of occupants' thermal sensation, which resulted to higher energy consumption than those based on estimated thermal sensation [1]. Some building automatic systems are also controlled based on the American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE) thermal comfort model, such as Predicted Mean Vote (PMV) [2]. These models mainly rely on empirical recommendations or predefined formulas, but do not take the individual's physiological characteristics into consideration [3–5]. Therefore, it is very important to accurately obtain an individual's thermal sensation and reflect it on the control logic of air-conditioning systems in real-time.

During the research, the human factors, such as clothing condition, active state and environmental preferences, always change in real-time, which will lead to unpredictable thermal sensation. In order to develop models to estimate personal thermal sensation, many researchers have used different physiological signals. Wang [6] used upper extremity skin temperatures, such as hand, finger, and forearm, to predict people's thermal state and explore the correlation between upper extremity skin temperatures and overall thermal sensation. Nakayama et al. [7] focused on the peripheral skin temperature for thermal sensation estimation and proposed an estimation method that can predict individual thermal sensation by monitoring the finger skin temperature. Sugimoto [8] proposed a wearable system to measure biological data, activity data and location data of humans in daily life. The wearable system consists of a tympanic temperature sensor, an electrocardiogram sensor with a tri-axial accelerometer and thermo-hygrometers, and

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skin temperature sensors. Ghahramani et al. [9] selected human face skin temperature as a physiological signal because of its high density of blood vessels. They presented a novel infrared thermography based technique to obtain an individual's thermal comfort and thermoregulation performance by monitoring several points of the face skin temperature. Xiong et al. [10] investigated seven local parts of human body to study the relationship between thermal perception and skin temperature under the condition of different transient thermal environments. Sim et al. [11] invented a wrist-type wearable device to simultaneously monitor the wrist skin temperatures, and they also assessed the feasibility of wrist skin temperature monitoring for human thermal sensation estimation. Zhang et al. [12] described a thermal sensation model based on skin temperature data measured from 19 individual body parts, and they have found that the local sensation would be related to both local and whole body skin temperature. Choi and Yeom [13,14] established a skin temperature-driven thermal sensation model by monitoring a significant and minimum number of the local body area. They also found the optimal combinations of local body segments that could represent the overall thermal sensation with a high degree of accuracy.

A large number of wrist-type wearable devices that can monitor physiological characteristics, such as wrist skin temperature and heart rate, have emerged and many researchers have focused on the feasibility of using wrist skin temperature to estimate human thermal sensation. Choi's research found that the wrist would be the most representative body location for thermal sensation estimation, but the estimation model that calculates based on wrist skin temperature was not given [15]. Sim et al. [11] verified the feasibility of wrist skin temperature in human thermal sensation estimation, and they developed some thermal sensation models by monitoring the wrist and fingertip skin temperatures. However, the studies have some limitations because the sample size was small and the finding may only be suited for the symmetric condition. Choi and Yeom [13] have found that the wrist skin temperature and its changing rates provided a higher accuracy than other body areas' skin temperature for the thermal sensation estimation when only a single body segment was considered.

However, these studies primarily focused on only one activity level, such as sedentary or minor activity. The human thermal comfort is subjective and multi-factor dependent and metabolic rate is one of the significant factors for thermal comfort [16,17]. Therefore, some of the research findings may be somewhat limited in different activity conditions. In addition, in order to reflect individuals' thermal sensation on the control logic of air-conditioning systems, the parameters of establishing thermal sensation estimation models should be obtained easily. Besides, it is really important to verify the feasibility of the estimation model in actual indoor environment because the actual automatic control of air-conditioning systems is an unstable environmental condition, which is different from the environmental chamber. Moreover, many studies have identified that heart rate is a potential indicator that can be used for thermal sensation estimation, but current human comfort models almost focus on skin temperature without considering the heart rate [18–20]. Choi et al. [19] demonstrated the possibility of using heart rate as a parameter for human thermal sensation estimation, but they did not develop any mathematical model.

Therefore, this paper aims at online monitoring of human thermal characteristics based on wristband device and developing the thermal sensation estimation models of the human body in different active states by experimental research in summer. This study also attempts to introduce the heart rate as another parameter for developing human thermal sensation estimation model under the different active states. The rest of this paper is organized as follows: Section 2 provides a description of experiment condition, including experiment chamber, equipment, experimental procedure, and methods of statistical analysis. Section 3 analyses the experimental results. Based on the study findings, this section also established several thermal sensation estimation models with different parameters. In addition, several tests were conducted in the actual built environment to verify the feasibility of correlation model in the unstable environmental condition. Section 4 discusses the obtained results and presents some limitations of this study as well. Section 5 lists the conclusions.

2. Methods

2.1. Experimental chamber and equipment

A series of human subjects experiments were carried out to collect human thermal sensation and thermal characteristics at the environment chamber of Dalian University of Technology in China. The floor plan of environment chamber, which consists of a 5.7 m × 6.3 m laboratory and a 2.8 m × 6.3 m HVAC system space, are illustrated in Fig. 1. The variable air volume (VAV) system was equipped to control the building thermal environment and indoor air quality.

In addition, many sensors were installed in the laboratory, including CO_2 sensor, air temperature and humidity sensor, and air velocity sensor. The temperature can be controlled within the range of 0.1 °C, which meets the requirements of control accuracy. The air velocity was controlled at less than 0.2 m/s, as suggested by ASHRAE Standard 55 [2]. In order to release the influence of indoor air quality, the concentration of CO_2 was controlled under 800 ppm according to ASHRAE Standards 62.1 [21]. The wristband device consists of a skin temperature sensor and a heart rate sensor, which can be used for online monitoring human thermal characteristics. All the temperature sensors are calibrated by the temperature verification box. The model and specification of all equipment are shown in Table 1.

2.2. Experimental procedure

The basic information about the participants, such as age, weight, height, body mass index (BMI), and gender were surveyed before the experiments. The information about the human subjects used for the final analysis is shown in Table 2.

Ten healthy subjects including six men and four women participated in this study. In order to minimize the influence of heat acclimation, all subjects were graduate students who have lived in Dalian for more than 2 years. Their physiological condition was normal, without any illnesses such as a cold or a fever. Their psychological condition was stable and had no mood swings during the experiments. The human subject experiments were carried out at least an hour after the subjects had eaten food or had done strenuous exercise. The overall flow chart of research is illustrated in Fig. 2. Since the target of this study is developing the correlation model between thermal sensation and thermal characteristics of human body under different active states for building thermal environment control, each subject wore a short sleeve T-shirt with no jacket and trousers during the experiments. The numerical value of the clothing insulation was approximately 0.57 clo.

The time schedule of experiments is shown in Fig. 3. Previous studies [13–15] have conducted the human sensation experiments under indoor temperature range of 20–30 °C. In these experiments, we also prepared to control the indoor temperature from 20 °C to 30 °C. However, some female subjects cannot bear too cold indoor temperature, thus we scrapped the experiment under the indoor temperature of 20 °C. The experiments were divided into two parts: cold condition (Fig. 3(a)) and warm condition (Fig. 3(b)). The indoor temperature decreased from 26 °C to 22 °C on the cold

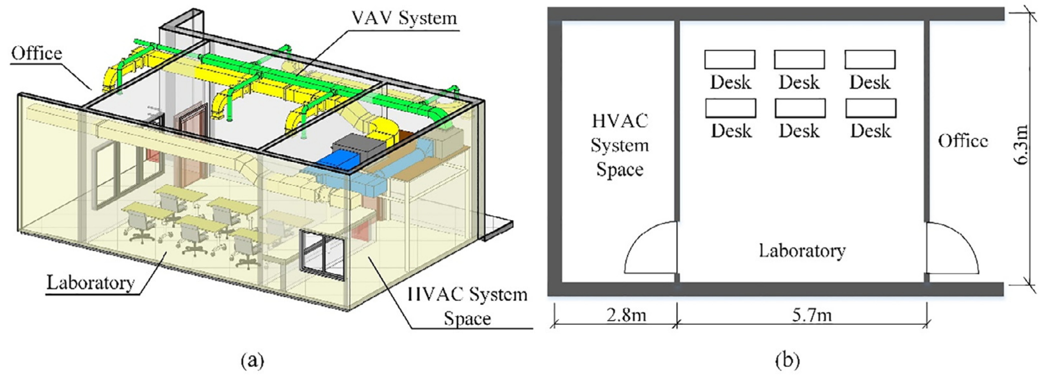

Fig. 1. Building model of environmental chamber: (a) 3D building model; (b) floor plan.

Table 1
Model and specification of all equipment.

Device	Model	Specification
Air temperature sensor	TS-FTD04	Accuracy: ±0.3 °C, Resolution: 0.1 °C
Air humidity sensor	TS-FTD04	Accuracy: ±3%, Resolution: 0.1%
CO_2 sensor	C7232A5810	Accuracy: ±30 ppm
Skin temperature sensor	HES-S3	Accuracy: ±0.3 °C, Resolution: 0.1 °C
Heart rate sensor	HXM-08L	Accuracy: ±3%
Temperature verification box	XLS-III	Accuracy: ±0.1 °C, Resolution: 0.1 °C

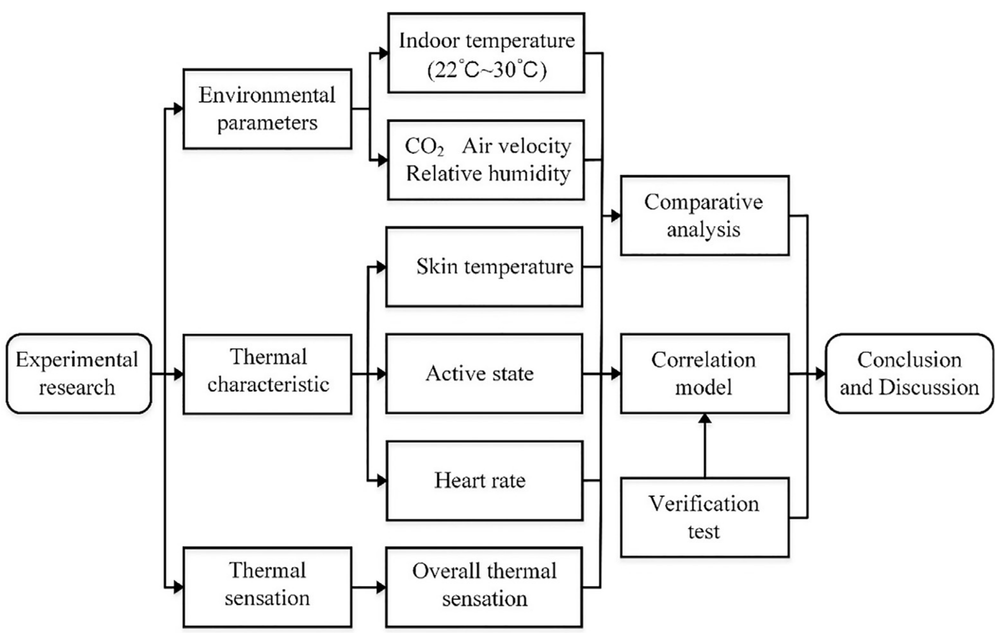

Fig. 2. Overall flow chart of research.

Table 2
Basic information about participants.

	Age	BMI	Number		
			Female	Male	Total
Value	23.60± 2.00	20.46 ± 1.76	4	6	10

condition and increased from 28 °C to 30 °C on the warm condition. As can be seen from Fig. 3, the initial indoor temperature was 26 °C, and the temperature changed 2 °C after every experiment. Thus, the experiments were carried out under the indoor temperature of 22 °C, 24 °C, 26 °C, 28 °C and 30 °C. During the first 20 min of the experiment, the subjects sit in the laboratory to adapt the environment. Then, they started to imitate three different active states. They were required to sit on the chair and read (1.0–1.2 Met) in sitting still state, walk (1.5–2.0 Met) in minor activity state, and deep squat or run (3.5–5.0 Met) in strenuous exercise state, respectively. Due to the activity intensity gradually increased on the same temperature condition, the last activity state might have a very little effect on the next one. Thus, the rest time between each active state on the same temperature condition could be set as any value. However, considering that their psychological and physiological conditions might be affected when they focus on one thing for long time, all the subjects had 10 min to rest and adjust themselves between each active state. Goto et al. [22] proved that subjective thermal responses tend to be steady after approximately 15–20 min under constant activity. Thus, the subjects rested 20 min after strenuous exercise and then proceeded to the next

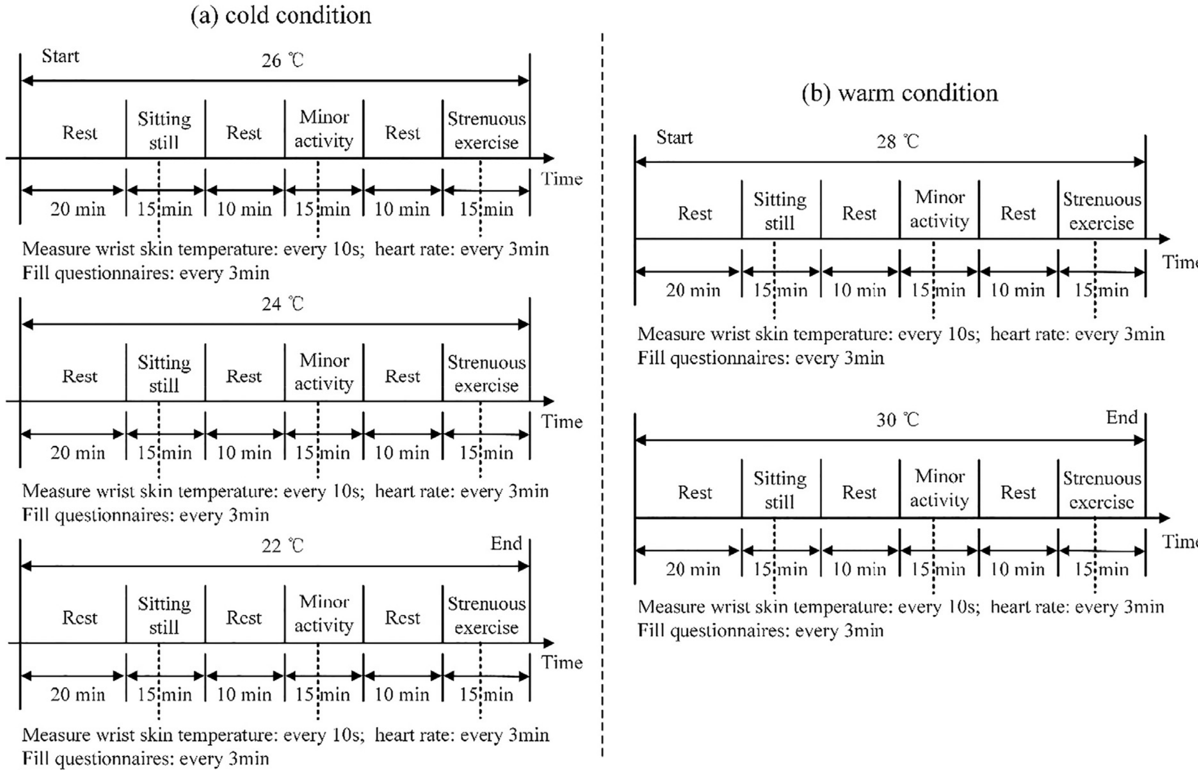

Fig. 3. Time schedule of experiments: (a) cold condition; (b) warm condition.

Table 3
Thermal sensation questionnaire with ASHRAE 7-point scale.

Thermal sensation	−3 Very cool	−2 Cool	−1 Slightly cool	0 Neutral	1 Slightly warm	2 Warm	3 Very warm

experiment condition. Based on the previous study [19,22], the subjects were asked to keep exercising for 15 min, and then filled out the questionnaires.

The environmental parameters, such as indoor temperature, relatively humidity, air velocity, and the concentration of CO_2 were recorded every 10 s. The wristband was worn on the human subject's left hand, which can monitor the wrist skin temperature and heart rate every 10 s and 3 min, respectively. The subjective perception of overall thermal sensation was assessed using ASHRAE 7-points scale [2] (Table 3). All the human subjects were asked to choose their subjective thermal sensation on the questionnaire every 3 min. In order to decrease the influence of indoor environment and human exercise intensity, all the participants were required to finish the tests simultaneously.

2.3. Statistical analysis method

The statistical methods were used to analyze collected data and obtain human thermal sensation estimation models. Regression analysis is a widely used statistical technique for investigating and modeling the relationship between different variables [23].

In this paper, multiple linear regression formula was used to analyze the mathematical relationship between human thermal characteristic (e.g., wrist skin temperature and heart rate) and thermal sensation. The multiple linear regression model is expressed by

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \tag{1}$$

where x_i is independent variable, y is dependent variable, β_i is the unit influence of x_i on y, and k is the number of regressor variables.

The coefficient of determination R^2 $(0 \le R^2 \le 1)$ is the most widely used index to evaluate the adequacy or goodness-of-fit of regression model, which can be expressed by

$$R^2 = \frac{\sum_{i=1}^{n} \left(\hat{y}_i - \bar{y}\right)^2}{\sum_{i=1}^{n} \left(y_i - \bar{y}\right)^2} \tag{2}$$

where y_i is the individual response at observation i, $\bar{y}$ is the mean value of y_i of the n observations, $\hat{y}_i$is the value of y estimated from the regression model for observation i. $R^2 = 1$ means a perfect fit, while $R^2 = 0$ indicates that either the model is unsuitable or no relationship exists. A more desirable goodness-of-fit measure is the corrected or adjusted R^2, computed as

$$\bar{R}^2 = 1 - (1 - R^2)\frac{n-1}{n-k} \tag{3}$$

where k is the number of regressor variables, and n is the total number of observation sets.

The root mean square error (RMSE) is usually used for estimation of the absolute error of the regressor model, which is defined as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{n-k}} \tag{4}$$

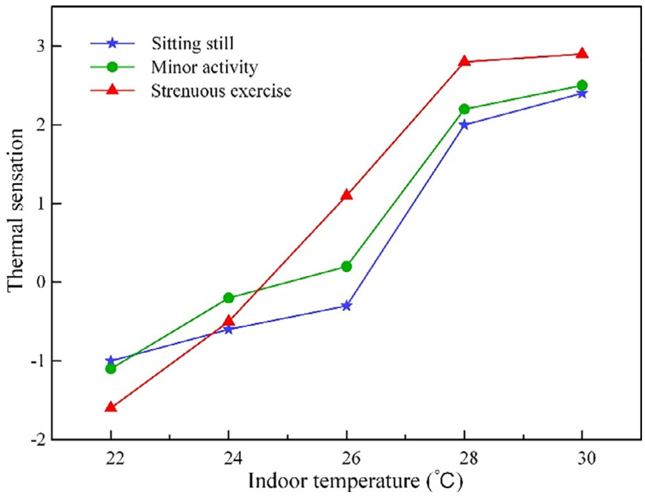

Fig. 4. Mean thermal sensation changes with increases in indoor temperature.

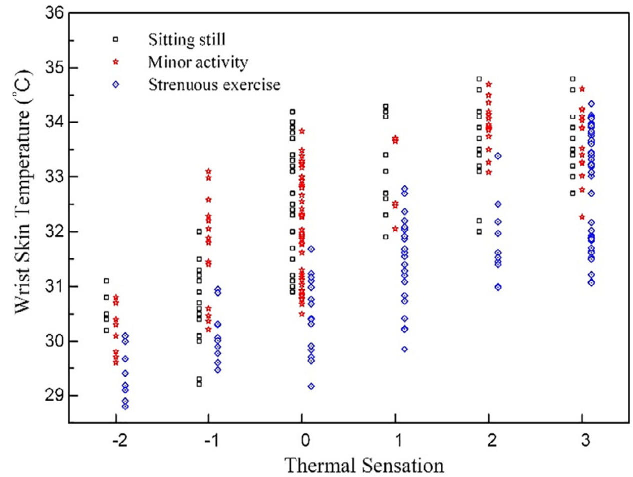

Fig. 5. Relationship between the wrist skin temperature and thermal sensation.

The RMSE is an absolute measure value and its value range is $0 \leq \text{RMSE} \leq \infty$. The unit of RMSE is the same as the y variable. The smaller the value of RMSE, the better fitting effect is realized.

In order to avoid over-fitting, cross-validation using the experimental data is used for model acquisition; this would better reflect the predictive capability of the model [23]. Therefore, the data was randomly divided into two partitions. First, 80% of the data was used to develop the model and calculate the internal predictive indices the coefficient of variation of the RMSE (CV) and normalized mean bias error (NMBE), which can be calculated as:

$$\text{CV} = \sqrt{\frac{\sum_{i=1}^{n} \left(y_{\text{i}} - \hat{y}_{\text{i}}\right)^2}{(n-k)}} / \bar{y} \tag{5}$$

$$\text{NMBE} = \frac{\sum_{i=1}^{n} \left(y_{\text{i}} - \hat{y}_{\text{i}}\right)}{(n-k) \times \bar{y}} \tag{6}$$

Then, the remaining 20% was used to calculate the y values by the already identified model and the external indices (CV and NMBE), which also can be calculated by Eqs. (5) and (6). We can then verify the accuracy of the predicted model by comparing internal predictive indices and external indices. Generally, the external indices will be poorer than the internal predictive indices, and a larger difference means greater over-fitting, and vice versa. After several adjustments and calculations, a relatively accurate model can be obtained.

3. Results

During the experiment, 2430 wrist skin temperatures and 405 heart rates were acquired from the wrist-type wearable devices. In addition, 405 thermal sensation votes were obtained from the questionnaire.

3.1. Effect of indoor temperature on thermal sensation

Fig. 4 shows the mean thermal sensation change with increases in indoor temperature. As the indoor temperature was increased from 22 °C to 30 °C, the thermal sensation level gradually increased under different activity states. However, the thermal sensation level under the strenuous exercise condition was lower than the sitting still condition and minor activity when the indoor temperature was in the cold condition (22–24 °C). On the contrary, the thermal sensation level under the strenuous exercise condition was obviously higher than the sitting still condition and minor activity when the indoor temperature was warm (26–30 °C). In the cold experiment, the temperature difference between indoor temperature and wrist skin temperature is relatively high, which caused the heat loss by wrist skin to be greater than the heat production of the human body by exercise. The more intense the activities get, the greater convective heat transfer coefficient of human skin and the more heat loss by human skin. Thus, when the indoor temperature was 22 °C, the mean thermal sensation under the condition of sitting still, minor activity and strenuous exercise were −1, −1.1, and −1.6, respectively. During the warm experiment, the temperature difference between indoor temperature and wrist skin temperature was relatively low. Even though the activities got intense, the convective heat transfer coefficient of the human skin became greater and more heat was lost by the human skin, but the heat production of the human body by exercise was higher than the heat loss by wrist skin. Thus, when the indoor temperature was 30 °C, the mean thermal sensation under the condition of sitting still, minor activity and strenuous exercise were 2.4, 2.5, and 2.9, respectively. These results indicate that indoor temperature had an effect on thermal sensation and that the activity state determined the degree of thermal sensation.

3.2. Relationship between wrist skin temperature and thermal sensation

Fig. 5 shows the scatter plot of wrist skin temperature by thermal sensation. Because very few of the subjects marked thermal sensation level −3 (very cool), the analyses only chose other thermal sensation levels except −3. It was clear that the thermal sensation level increased from −2(cool) to 3(very warm) with an increase in the wrist skin temperature, which means that the wrist skin temperature reflected the human thermal sensation to some extent. Moreover, Fig. 5 illustrates that the wrist skin temperature on the condition of strenuous exercise seemed lower than in sitting still and minor activity under the same thermal sensation level.

The error interval plots of wrist skin temperature by thermal sensation in different active states are shown in Fig. 6. When the thermal sensation level varied from −2(cool) to 3(very warm), the mean wrist skin temperature on the condition of sitting still ranged from 30.6 °C to 33.7 °C; for minor activity, it ranged from 30.3 °C to 33.4 °C; and for strenuous exercise, it ranged from 29.4 °C to 32.9 °C. The large difference in wrist skin temperature indicated that each individual generated a different wrist skin

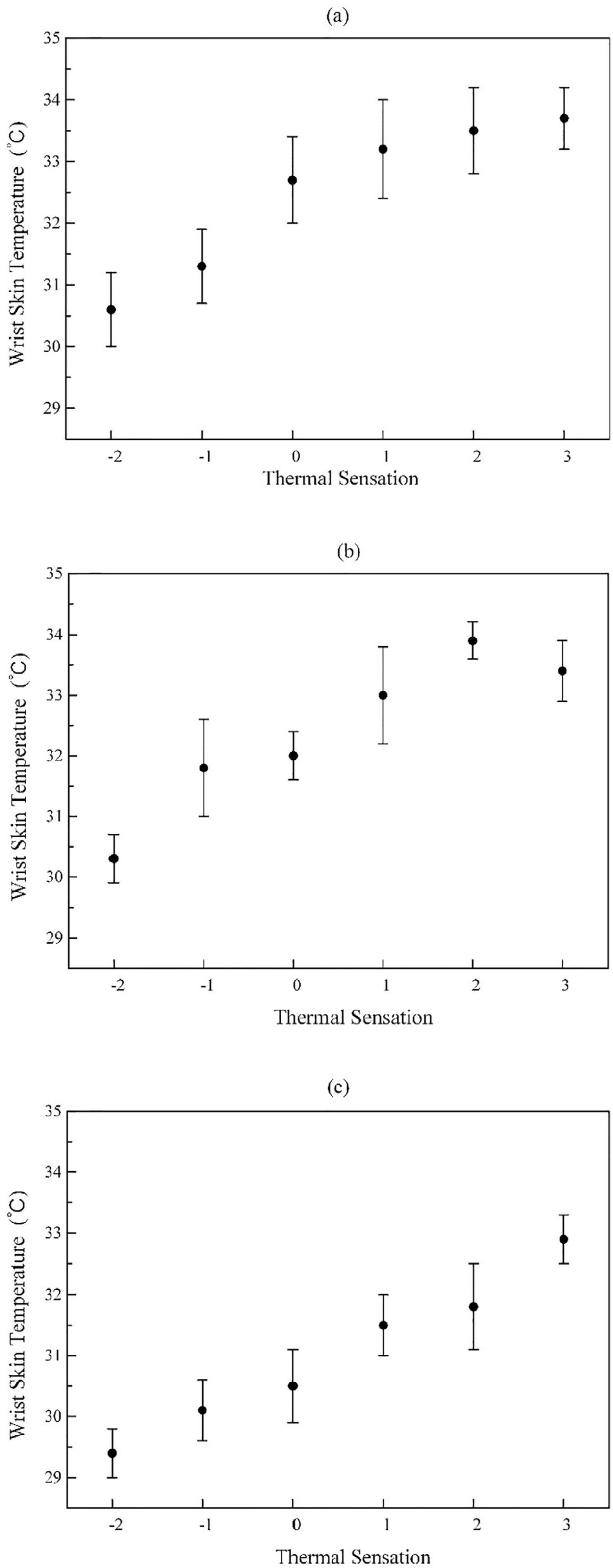

Fig. 6. Error interval plot of wrist skin temperature by thermal sensation in different active state: (a) sitting still; (b) minor activity; (c) strenuous exercise.

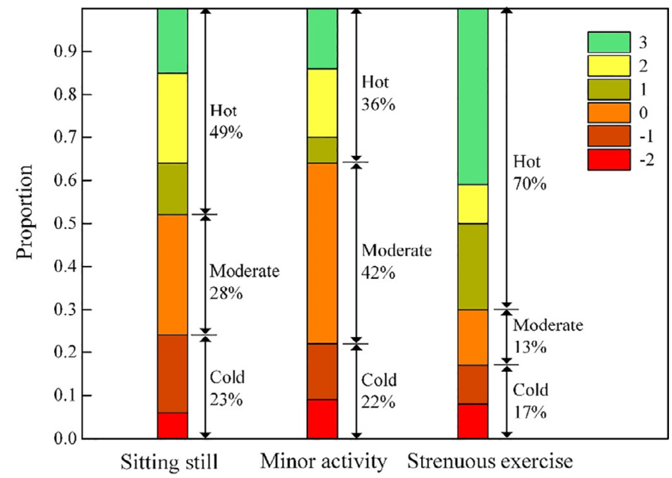

Fig. 7. Proportion of thermal sensation in different active states.

temperature, even though they were exposed to the same indoor temperature. With the activity state became more and more strenuous, the wrist skin temperature also had a large variation. Furthermore, the human thermal sensation is a subjective evaluation. The human subjects may have different thermal sensation votes under the same wrist skin temperature. Therefore, the results revealed a large difference in wrist skin temperature for a certain value of TSV. Fig. 6 shows that the mean wrist skin temperature decreased as the human activity state became more and more strenuous. Besides, the results illustrated that thermal sensations increased as the mean wrist skin temperature rose, although the mean wrist skin temperature at thermal sensation level 2(warm) appeared higher than that of thermal sensation level 3(very warm). Therefore, we can conclude that the human thermal sensation correlated positively with the wrist skin temperature, and the quantitative analysis will be given in Section 3.4.

3.3. Comparison of heart rate and thermal sensation

Many studies [22,24,25] pointed out the significant relationship between human thermal sensation and human metabolic rate. Goto et al. [19] proposed a model that can estimate transient thermal sensation after metabolic step-changes. Thus, it is prudent to assume that the human thermal sensation is significantly correlated with human metabolic rate, which depends on activity levels. For example, humans may feel hot when they are running, and they may feel cold when they are sitting still under the same indoor environment. Fig. 7 illustrates the proportion of thermal sensation in three different active states. The thermal sensation level from 1(slightly warm) to 3(very warm) meant the subjects were feeling hot, and the proportion of hot sensation were 49%, 36%, and 70%, respectively. The thermal sensation level from −2(cool) to −3(slightly cool) meant the subjects were feeling cold, and the proportion of cold sensation was 23%, 22%, and 17%, respectively. Obviously, due to the increase of metabolic rate under the condition of strenuous exercise, the proportion of hot thermal sensation was much higher than other activity levels, and the proportion of cold thermal sensation was lower than others. The results illustrate that the activity levels had a great influence on thermal sensation, and the human thermal sensation estimation models should take the activity level into consideration.

Different activity levels will seriously affect the heart rate. Thus, it may be natural to have various levels of heart rate under different activity levels. The error interval plot of heart rate by thermal sensation in different active states is shown in Fig. 8. The variation ranges of the mean heart rate are 75–83 bpm, 85–99 bpm, and

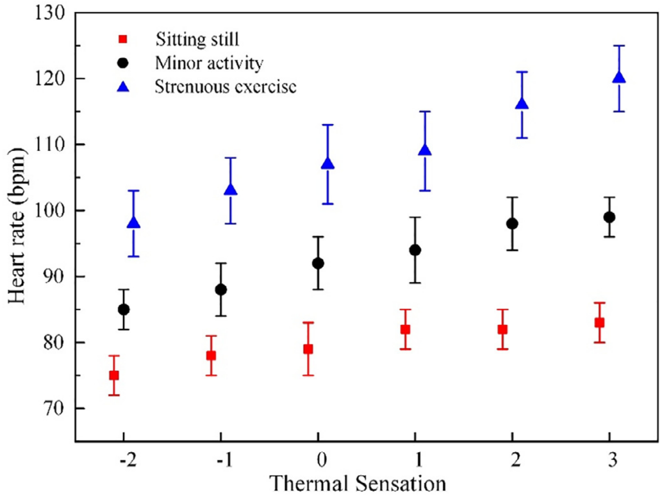

Fig. 8. Error interval plot of heart rate by thermal sensation in different active states.

98–120 bpm (beat per minute) for the condition of sitting still, minor activity, and strenuous exercise, respectively. The heart rate increased with an increase in thermal sensation levels in different activity states, especially on the condition of strenuous exercise, which illustrates that the heart rate was positively correlated with the thermal sensation. Combined with Fig. 7, the experimental results demonstrated that it is possible to use the heart rate as a variable for thermal sensation estimation. The quantitative analysis between heart rate and thermal sensation will be analyzed in the next section.

3.4. Evaluation method and verification of thermal sensation

From the experimental results, we now know that the human thermal sensation is affected by indoor temperature, wrist skin temperature and heart rate. Due to the indoor temperature having a positive relationship with the wrist skin temperature, it is incorrect to consider both indoor temperature and wrist skin temperature as variables when developing the thermal estimation models using multiple linear regression model. In addition, previous studies [11,26] have demonstrated that the human sensation has a relationship with the time differential of the wrist skin temperature. Therefore, this section aims to develop the mathematical models relating human thermal sensation, wrist skin temperature and its time differential, and heart rate. To develop the thermal sensation models, 80% of the data was used, and the rest were used to validate the models.

At first, we developed the thermal sensation models in different activity states. In this condition, the equation only included wrist skin temperature and its time differential, and the linear regression is based on Eq. (7)

$$\mathrm{TSV} = a + bT_{\mathrm{wsk}} + cD_{\mathrm{wsk}} \tag{7}$$

where, TSV is the thermal sensation vote, which is used for assessing the degree of human thermal sensation. T_{wsk} is the mean skin temperature of the wrist, and *D*wsk is the time differential of the wrist skin temperature. The regression coefficient of estimation models are shown in Table 4. The data used for the model development was based on all the participants, and the time differential of wrist skin temperature (*D*wsk) was calculated as the difference of the wrist skin temperature between the last 10 s and the initial 10 s of every 3 min in the same activity levels and temperature condition. The CV and NMBE values of the prediction models indicated that these models can provide good predictions without over-fitting. In order to compare and evaluate the performance of the thermal sensation estimation models, the correlation coefficient, adjusted *R*2 and RMSE of each model were calculated. As shown in Table 4, the thermal sensation estimation model in strenuous exercise showed the highest accuracy among the models, and the adjusted *R*2 was above 94% both in sitting still and minor activity. Moreover, the RMSE of all the models were less than 1, which means that the thermal sensation estimation models had a good prediction effect.

In Section 3.3, we analyzed the relationship between heart rate and activity state, and found that the heart rate was a potential parameter for thermal sensation estimation. Therefore, we added the heart rate in the thermal sensation equation, and the mathematical model is expressed by

$$\mathrm{TSV} = a + bT_{\mathrm{wsk}} + cD_{\mathrm{wsk}} + dH_{\mathrm{R}} \tag{8}$$

Table 5 summarizes the regression coefficients and performance evaluation indexes of the overall models. The first thermal sensation estimation model had the following parameters: wrist skin temperature and its time differential, and heart rate. The value of significance tending to zero means high correlation. The CV and NMBE values of the prediction models indicated that the model can provide good predictions without over-fitting. Even though the correlation coefficient and adjusted *R*2 of the overall model was less than the models in different activities, it still had a good regression performance. The RMSE was 0.597, which also illustrated the high accuracy in the thermal sensation estimation. To find which variables are important in making the prediction, the standardized regression coefficients were calculated. In a multiple regression model, the standardized regression coefficients are used to state the relative importance of all regressor variables. The smaller the value of standardized regression coefficients, the less importance of the regressor variables.

$$\beta_{\mathrm{j}}{}' = \beta_{\mathrm{j}} \times \frac{\sigma_{\mathrm{x}}}{\sigma_{\mathrm{y}}} = \beta_{\mathrm{j}} \times \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{\mathrm{i}}-\bar{x})^2} \Big/ \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{\mathrm{i}}-\bar{y})^2} \tag{9}$$

where $\beta_{\mathrm{j}}{}'$is the standardized regression coefficients, σ_{x} is the standard deviation of *x*, σ_{y} is the standard deviation of *y*, x_{i} is independent variable, *y* is dependent variable, β_{j} is the unit influence of x_{j} on y, and *n* is the total number of observation sets. The absolute value of the standardized regression coefficients directly reflects the influence of x_{i} on *y*. In the overall thermal sensation estimation model, the standardized regression coefficients of wrist skin temperature, time differential of wrist skin temperature, and heart rate were 0.95, 0.53 and 0.88, respectively. The results revealed that the significance of time differential of wrist skin temperature was less than the wrist skin temperature and heart rate. Thus, we also developed a thermal sensation estimation model without the time differential of wrist skin temperature, which is shown in line 2 of Table 5. The correlation coefficient was 0.941 and the adjusted R^2 was 0.87. The thermal sensation estimation model based on wrist skin temperature and heart rate showed the relatively high accuracy.

From the above discussion, we got the results that the proposed models can be used to estimate the thermal sensation in stable environmental condition. In order to verify the feasibility of the correlation model in the unstable environmental condition, several tests were conducted in the actual built environment. Since the target of this study is to develop thermal sensation estimation model for the control of building thermal environment, the tests were chosen in built environment that controlled by air-conditioning system. Firstly, the participants were required to sit in an office and perform office work to represent the sitting still state. Second, they were required to walk in a shopping mall to represent the minor activity state. Third, they were required to

Table 4
Thermal sensation estimation models and its performance in different activity states.

Activity state	Regression coefficient			Sig.	Correlation coefficient	Adjusted R^2	RMSE	Internal indices		External indices	
	a	b	c					CV	NMBE	CV	NMBE
Sitting still	−19.549	0.598	9.293	0.005	0.985	0.950	0.361	0.118	0.103	0.082	0.065
Minor activity	−23.084	0.751	7.553	0.007	0.982	0.940	0.396	0.134	0.107	0.088	0.080
Strenuous exercise	−29.638	1.034	6.552	0.000	0.999	0.995	0.114	0.063	0.047	0.042	0.039

Table 5
Overall thermal sensation estimation models and their performance.

No.	Regression coefficient				Sig.	Correlation coefficient	Adjusted R^2	RMSE	Internal indices		External indices	
	a	b	c	d					CV	NMBE	CV	NMBE
1	−50.259	1.330	0.748	0.088	0.000	0.944	0.868	0.597	0.098	0.082	0.027	0.070
2	−50.390	1.347	–	0.082	0.000	0.941	0.870	0.613	0.074	0.062	0.051	0.055

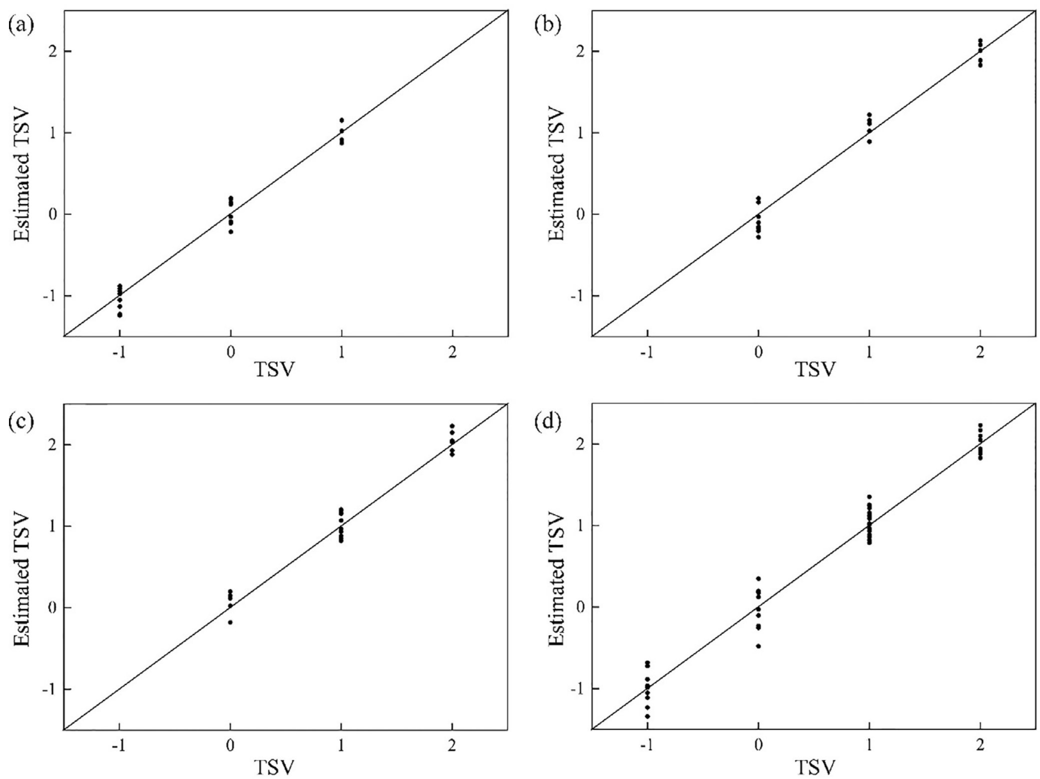

Fig. 9. Comparison of actual thermal sensation and estimated thermal sensation in the actual built environment: (a) sitting still model; (b) minor activity model; (c) strenuous exercise model; (d) overall model.

exercise in a gym and run on the treadmill to represent the strenuous exercise. During the first 20 min of every experiment, the subjects adapted to the environment and then the test began. Every test was done for half-an-hour. During the experiments, each subject wore a short sleeve T-shirt with no jacket and trousers, so that the numerical value of the clothing insulation was approximately 0.57 clo. The equipment and frequency of data collection were the same as the experiments in artificial climate chamber. The parameters of wrist skin temperature and heart rate were recorded every 10 s and 3 min, respectively. The subjective thermal sensation was chosen on the questionnaire every 3 min.

Fig. 9 illustrates the relationship between the actual thermal sensation and estimated thermal sensation. Fig. 9(a)–(c) show the results that calculated the estimated TSV by using the thermal sensation estimation model in sitting still, minor activity, and strenuous exercise, respectively. In these three models, the estimated TSV only determined by wrist skin temperature and its time differential. Fig. 9(d) calculated the estimated TSV by using the overall thermal sensation estimation model, which includes the parameters of wrist skin temperature and its time differential, and heart rate. In Fig. 9, the estimated thermal sensation based on the proposed models was close to the actual thermal sensation. The actual thermal sensation is a fuzzy value. As long as the difference between the predicted value and the actual value is less than 0.5, we can consider the prediction results to be accurate. Therefore, the proposed models in this paper can be used for an unstable environmental condition, which means that these models can accurately estimate the human thermal sensation in actual building environment and can also be used for automatic control of the building thermal environment in the future.

4. Discussion

As illustrated in Section 3, the statistical analysis and correlation analysis suggested that the wrist skin temperature and its time differential and the heart rate can be used for estimating thermal sensation with a high degree of accuracy in the different activity states. Moreover, the results of this study indicated the promising applicability of obtaining correlation models in the unstable environmental condition. Takada et al. [26] conducted human subject experiments and proposed an equation for estimating whole-body thermal sensation based on mean skin temperature and its time differential. The results obtained in our study concur with the results presented by these authors. Choi et al. [19] proved the possibility of using heart rate as a parameter for estimating human thermal sensation. However, they did not develop any mathematical model. This paper used heart rate as a variable to develop thermal sensation estimation models and confirmed Choi' s research results. Many studies [7–9,11,17] primarily focused on only one activity level or moderate activities, which limited the application scope of the thermal sensation models. This study is meaningful in that it demonstrated the possibility of using the wrist skin temperature and its time differential as well as the heart rate for thermal sensation estimation in different activity states, which increased the application scope of the models. In addition, the results of this study also demonstrated the promising applicability of obtained correlation models in the unstable environmental condition, which showed the application potential of this study for automatic control logic of the building thermal environment as an input to optimize the set-point of supply air temperature or supply airflow of the central air-conditioning system so that it can meet the requirements of human thermal comfort.

Many previous studies [3,4,13,14,27] have demonstrated that gender has a huge influence on human thermal sensation. In this study, the variation range of mean wrist skin temperature are 31.4–33.1 °C and 31.0–33.6 °C in female and male group, respectively. In the male group, the wrist skin temperature increased continuously with the increase of thermal sensation, which showed a positive relationship between wrist skin temperature and thermal sensation. However, the wrist skin temperature did not show a significant positive correlation with thermal sensation in the female group. Due to the small sample size, it is difficult to get the accurate results of the gender differences. Further research is required to analysis the influence of gender to human thermal sensation in detail.

In spite of the significant research results of this study, there are still some limitations. First, this study used only 10 human subjects as experimental samples. Even though this sample size and experimental data are feasible and meaningful for the statistical analysis and correlation analysis, additional human subject tests would increase the validity and accuracy of the results. In addition, the correlation analysis and model development did not consider the physiological characteristics of the human subjects, such as gender and body mass index. Furthermore, the experiment was conducted in summer, the models may not be suited for estimating thermal sensation in winter. Accordingly, further studies are required to study the human thermal sensation estimation models in different seasonal conditions with a larger number of human subject experiments that may increase the validity of the models.

5. Conclusions

In this paper, an intelligent wristband device is used for monitoring human thermal characteristics and a series of human subject experiments are carried out for developing the thermal sensation estimation model of the human body in the different active states in summer. Based on this research, we made the following conclusions:

- The indoor temperature has an effect on thermal sensation, and the activity state determines the degree of thermal sensation. The human thermal sensation correlated positively with the wrist skin temperature and it is possible to use the heart rate as a variable for thermal sensation estimation.
- The wrist skin temperature and its time differential are used as variables in developing the thermal estimation models by using multiple linear regression models. The thermal sensation estimation model in strenuous exercise shows the highest accuracy among the models, and the adjusted R^2 is above 94% both in sitting still and minor activity. Moreover, the RMSE of all models are less than 1, which means that the thermal sensation estimation models have good prediction effect.
- The thermal sensation estimation models using wrist skin temperature and its time differential, and heart rate as parameters have a correlation coefficient of 0.944. The correlation coefficient of thermal sensation estimation model based on the wrist skin temperature and heart rate is 0.941 and the adjusted R^2 is 0.87, which shows a relatively high accuracy in thermal sensation estimation.
- The proposed models can be used for unstable environmental condition by several verification tests in actual built environment, which implies that these models can accurately estimate the human thermal sensation in actual building environment and can be used for automatic control of the building thermal environment in the future.

Conflict of interest

Declarations of interest: None.

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